Space Optimization Design of Building Environment Based on Particle Swarm Optimization Neural Network

Ling Xia
Hunan University of Arts and Science, Changde, 415000 Hunan, China

Keywords: Particle Swarm Optimization Theory, Particle Swarm Optimization Neural Network, Space, Optimize Design, Built Environment.

Abstract: Space optimization design plays an important role in the space of intelligent building environment, but there is a problem of inaccurate optimization positioning. Traditional deep learning cannot solve the spatial optimization problem in the space of intelligent building environment, and the effect is not satisfactory. With the continuous advancement of artificial intelligence technology, its application in architectural design and management is becoming more and more extensive. Especially in the field of spatial optimization of the built environment, the combination of particle swarm optimization (PSO) algorithms and neural network technology is gradually changing the way we design and use built spaces. This intelligent approach not only improves energy efficiency and functionality, but also leads to a more comfortable and healthy environment for occupants and occupants.

1 INTRODUCTION

Firstly, the particle swarm optimization algorithm imitates the group behavior of bird hunting and fish predation in nature, and finds the optimal solution to the problem through information sharing between individuals (Zhang and He, et al.2023). When this algorithm is applied to spatial optimization in the built environment, each "particle" represents a possible solution (Wang and Liu, et al.2023). These solutions include the layout of the building, lighting, ventilation, and many other factors that affect comfort and efficiency (Guo and Dong, et al.2023). By simulating the flight patterns of individuals in a flock of birds, the particle swarm moves in the solution space, explores and eventually converges to the optimal or near-optimal architectural design scheme (Liu and Sun, et al.2023).

2 RELATED CONCEPTS

2.1 Mathematical Description of a Particle Swarm Optimization Neural Network

Neural networks, on the other hand, provide a powerful machine learning tool that can analyze and learn from large amounts of data to predict the impact of different design decisions on building performance (Shi and Fu, et al.2023). In the process of spatial optimization of the built environment, it can be used to simulate and evaluate the design scheme represented by various particles, so as to guide the particle swarm optimization algorithm to search for the best solution more efficiently (Wang and Zhang, et al.2023).

$$\lim_{x\to\infty}(y_i \cdot t_{ij}) = \lim_{x\to\infty} y_{ij} \geq \max(t_{ij} \div 2) \quad (1)$$

Among them, the judgment of outliers is shown in Equation (2).

Xia, L.
Space Optimization Design of Building Environment Based on Particle Swarm Optimization Neural Network.
DOI: 10.5220/0013538200004664
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 1*, pages 194-199
ISBN: 978-989-758-763-4

$$\max(t_{ij}) = \partial(t_{ij}^{\ 2} + 2 \cdot t_{ij}) \succ mean(\sum t_{ij} + 4)\mathrm{M} \tag{2}$$

Combining the technology of particle swarm optimization algorithms and neural networks, it can handle extremely complex optimization problems.

To sum up, the combination of particle swarm optimization algorithm and neural network is not only a technical innovation, but also represents the trend of spatial optimization of the built environment to be more intelligent and automated (Guo and Zhang, et al.2023). As technology matures and becomes more popular, the buildings of the future will become smarter and more able to meet human needs for comfort, health and efficient energy use (Zhang, 2023). This is not only an innovation in the construction industry, but also a profound improvement and promotion of the human living environment and adjusting building orientation to reduce heat loss (Hu, Li, et al.2023). Traditional solutions to these complex problems often rely on the designer's empirical judgment and trial-and-error process, but now, intelligent algorithms can provide multiple efficient solutions for designers to choose from in a short period of time..

$$F(d_i) = \square \sqrt{b^2 - 4ac} \sum t_i \bigcap \xi \cdot \sqrt{2} \to \boxed{\int} y_i \cdot 7 \tag{3}$$

2.2 Selection of Space Optimization Design Scheme

In addition, by continuously collecting real-world operating data from the building and feeding it back to the neural network for learning and model iteration, this approach is able to continuously improve and adapt to new design challenges (Yang and Li, 2023).

$$g(t_i) = \ddot{x} \cdot z_i \prod F(d_i) \frac{dy}{dx} - w_i \tag{4}$$

This adaptive nature allows the building to remain in optimal condition throughout its lifecycle, which is critical to improving the overall efficiency of the building and reducing maintenance costs.

$$\lim_{x \to \infty} g(t_i) + \lim_{x \to \infty} F(d_i) \le \bigcap \frac{1}{2} \max(t_{ij}) \tag{5}$$

To improve the effectiveness of the space optimization design reliability, all data needs to be standardized and the result is shown in Equation (6).

$$\boxed{g(t_i}) + F(d_i) \leftrightarrow mean(\sum t_{ij} + 4) \tag{6}$$

2.3 Analysis of Space Optimization Design Scheme

Before the particle swarm optimization neural network, the spatial optimization design scheme should be analyzed in all aspects, and the spatial optimization design requirements should be mapped to the spatial optimization design library, and the unqualified spatial optimization design scheme should be $No(t_i)$ eliminated. According to Equation (6), the anomaly evaluation scheme can be proposed, and the results is shown in Equation (7).

$$No(t_i) = \frac{\boxed{g(t_i}) + F(d_i)}{mean(\sum t_{ij} + 4)} \frac{n!}{r!(n-r)!} \tag{7}$$

Among them, it is $\frac{\boxed{g(t_i}) + F(d_i)}{mean(\sum t_{ij} + 4)} \le 1$ stated that the scheme needs to be proposed, otherwise the scheme integration is $Zh(t_i)$ required, and the result is shown in Equation (8).

$$Zh(t_i) = \Phi\pi[\sum \boxed{g(t_i}) + F(d_i)] \tag{8}$$

For example, in a real building environment space optimization project, the combination of particle swarm optimization algorithm and neural network can output the most energy-efficient and comfortable indoor layout after considering multiple factors of the internal and external environment of the building (Wu Jigang and Wen Gang, 2023). At the same time, the technology can also adjust the operating parameters of the building in real time and respond to changes in the external environment, such as weather changes or changes in usage patterns, so as to achieve the purpose of dynamic optimization.

$$accur(t_i) = \frac{\min[\sum g(t_i) + F(d_i)]}{\sum g(t_i) + F(d_i)} \times 100\% \tag{9}$$

In the vast arena of modern architectural design and planning, an algorithm called "Particle Swarm Optimization" (PSO) has quietly emerged. This algorithm originated from the study of bird predatory behavior, and now it has become an indispensable intelligent tool in the design of built environment spaces. With its unique advantages, it plays an important role in optimizing energy efficiency, rationalizing space layout, and improving environmental comfort.

$$accur(t_i) = \frac{\min[\sum g(t_i) + F(d_i)]}{\lim_{x \to \infty} \sum g(t_i) + F(d_i)} + \sqrt{2} randon(t_i) \tag{10}$$

Spatial design in the built environment is a complex decision-making process with multiple factors and objectives. Traditional methods rely on the experience and intuition of designers, and it is often difficult to reach an optimal solution. However, the particle swarm optimization algorithm provides a completely new solution.

3 OPTIMIZATION STRATEGY FOR SPACE OPTIMIZATION DESIGN

Specifically, when applying PSO to optimize the space of the built environment, it is first necessary to clarify the optimization goals, such as reducing energy consumption, improving the efficiency of space use, or enhancing the comfort and aesthetics of indoor and outdoor environments. This is followed by a series of constraints, including building codes, cost control, material properties, etc. The particle swarm algorithm will find a balance between these goals and constraints to find the best design solution.

3.1 Introduction to Space Optimization Design

By simulating the foraging behavior of a flock of birds, the algorithm uses a swarm of "particles" to explore in the design space, each particle represents a potential solution, and the interaction and learning mechanisms between the particles continuously push the whole flock to evolve in the direction of a better solution.

Table 1: Space-optimized design requirements

Scope of application	Grade	Accuracy	Space-optimized design
Revidential construction	I	85.00	78.86
	II	81.97	78.45
Commercial building	I	83.81	81.31
	II	83.34	78.19
Educational building	I	79.56	81.99
	II	79.10	80.11

The space-optimized design process in Table 1 is shown in Figure 1.

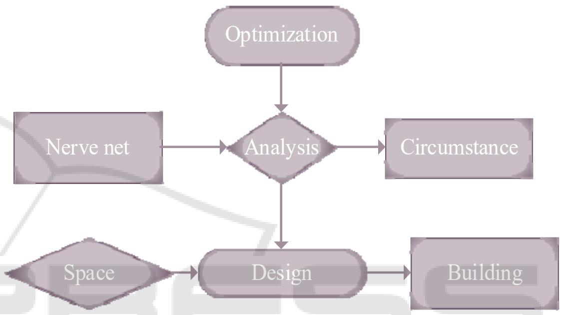

Figure 1: Analysis process for space-optimized design

It is worth mentioning that the PSO algorithm is able to deal with nonlinear, multimodal complex problems. This makes it extremely resilient and adaptable in the face of changing building environments and individual design requirements. Whether it is the spatial planning of commercial complexes, the environmental layout of residential areas, or even the optimization of energy consumption systems for large public buildings, PSO can provide strong decision support.

3.2 Space Optimization Design

In addition, with the advancement of computer technology and the enhancement of data analysis capabilities, PSO algorithms can be combined with geographic information systems (GIS), building information modeling (BIM) and other intelligent algorithms to form a more powerful decision-making framework. This integrated application not only improves design accuracy, but also significantly shortens the design cycle, enabling construction projects to be completed in less time and with higher quality.

Table 2: The overall picture of the space optimization design scheme

Category	Random data	Reliability	Analysis rate
Revidential construction	85.32	85.90	83.95
Commercial building	86.36	82.51	84.29
Educational building	84.16	84.92	83.68
Mean	86.84	84.85	84.40
X6	83.04	86.03	84.32
		P=1.249	

Table 3: Comparison of spatial optimization design accuracy of different methods

Algorithm	Survey data	Space-optimized design	Magnitude of change	Error
Particle swarm optimization neural networks	85.33	85.15	82.88	84.95
Deep learning	85.20	83.41	86.01	85.75
P	87.17	87.62	84.48	86.97

3.3 Space Optimization Design and Stability

Despite the many advantages of PSO algorithms, their application in the spatial design of the built environment still faces some challenges. For example, how to transform the abstract data generated by the algorithm into practical and actionable design solutions, and how to deal with various uncertainties and variability in practical applications.

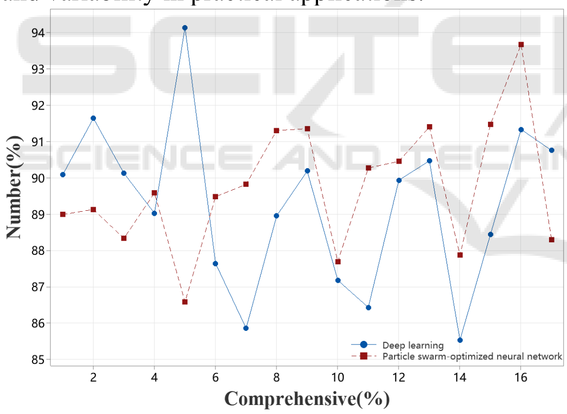

Figure 2: SPACE optimization design of different algorithms

In summary, the application of particle swarm optimization algorithm in the spatial design of the built environment is increasingly becoming a force to be reckoned with. It greatly improves the scientific and practical design through intelligence and automation, and opens up a new way to create a more energy-saving, efficient, comfortable and livable building environment. With the further development and application of future technology, the particle swarm optimization algorithm will surely bloom more dazzling in the field of architecture.

Therefore, future research and development efforts need to be made in the improvement of the algorithm itself, the deep integration with other technologies, and the flexibility in practical applications.

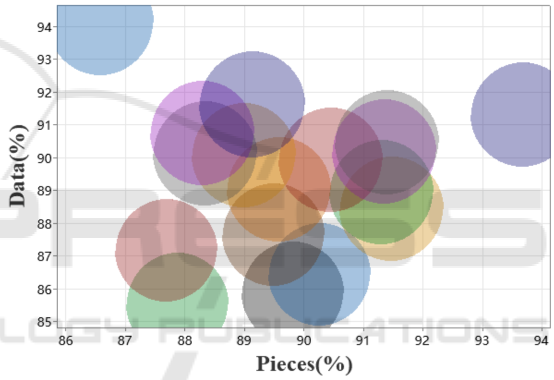

Figure 3: Spatially optimized design of particle swarm optimization neural network

We are entering a new era driven by data and algorithms. In the field of architecture, algorithms have become an important force for design innovation. Not only do they reshape the way we perceive spaces in the built environment, but they also offer the possibility to create more efficient, sustainable and personalized spaces. In this article, we will explore how algorithms are revolutionizing the built environment and how they can impact architects' design philosophy, construction process, and user experience.

3.4 Rationality of Space Optimization Design

First of all, the algorithm makes architectural design more scientific and efficient through its precise data processing and pattern recognition capabilities.

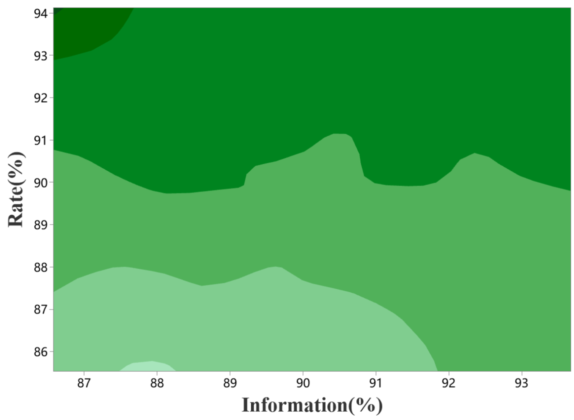

Figure 4: Space optimization design of different algorithms

Second, algorithms make custom designs feasible and economical. In the past, customization often meant high cost and time investment, but the application of algorithms has changed all that. Through algorithm-assisted design, architects are able to quickly generate personalized solutions based on the specific needs and preferences of users. Whether residential, commercial, or public spaces, algorithms are able to provide unique design solutions that meet the unique requirements of different clients.

3.5 The Effectiveness of Space-Optimized Design

Traditionally, architectural design has been a complex creative process involving numerous variables and uncertainties.

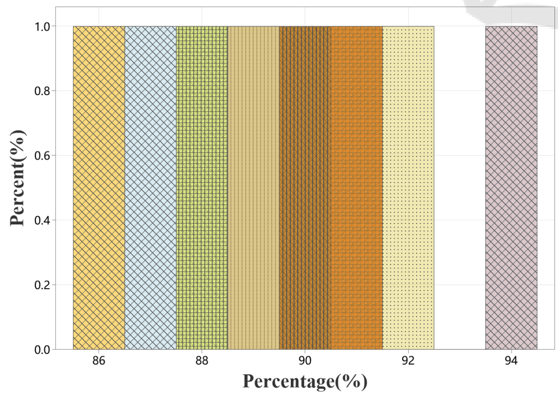

Figure 5: Space optimization design of different algorithms

Furthermore, algorithms play a vital role in the building construction process. The construction industry is facing labor shortages and pressure to improve efficiency, and algorithm-powered automation and robotics solutions are changing that. For example, algorithms can help plan construction sequences, optimize material allocation, and even play a central role in 3D printed buildings. This not only improves the speed and accuracy of construction, but also reduces the labor intensity of workers and promotes the modernization of the entire industry.

With the help of algorithms, architects can simulate multiple design scenarios and predict the effects of various factors such as lighting, ventilation, and structural stability. For example, by using computational design tools, the energy performance of buildings can be optimized at an early stage, reducing the time and cost of subsequent adjustments.

Table 4: Comparison of the effectiveness of spatial optimization design of different methods

Algorithm	Survey data	Space-optimized design	Magnitude of change	Error
Particle swarm optimization neural networks	82.21	85.92	84.59	82.85
Deep learning	83.73	84.23	84.41	83.55
P	84.20	87.39	84.76	83.90

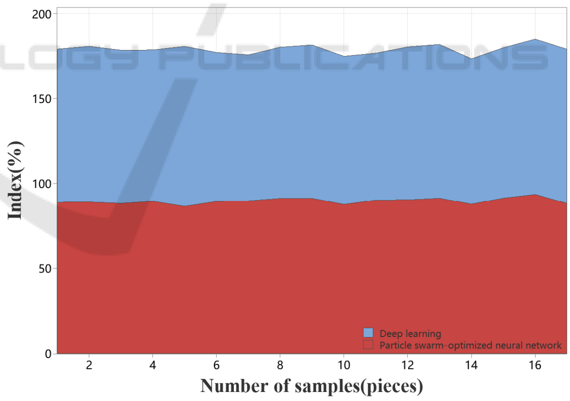

Figure 6: Particle swarm optimization neural network space optimization design

Finally, algorithms are revolutionizing the design of the built environment in terms of how they affect the way we experience and interact. With the development of virtual reality (VR) and augmented reality (AR) technologies, algorithms can create immersive, simulated environments that allow users to experience spaces before buildings are built. This provides designers with valuable user feedback and fosters a strong connection between the design and the user's needs. In short, in the creation and evolution of the built environment, algorithms are not only an auxiliary tool, but a revolutionary force that cannot be ignored. With its limitless potential, it is driving the development of the construction sector in a more efficient, sustainable and individual direction. The architecture of the future will no longer be just static structures, they will be dynamically evolving ecosystems, carefully woven from data and algorithms. As experts and enthusiasts in the field of architecture, we should embrace this change and jointly build the future space of human life

4 CONCLUSIONS

In addition, the maintenance and management of the built environment has become more intelligent thanks to algorithms. Through real-time analysis of large amounts of data, algorithms can help managers monitor the performance of buildings, predict maintenance needs, and automatically adjust systems to improve efficiency. Intelligent building management systems learn from user behavior patterns and make adjustments accordingly, such as adjusting indoor temperature or lighting intensity, to provide users with a more comfortable living and working environment.

REFERENCES

Zhang Yu, He Xiaoxing, Sun Xiwen. Prediction Analysis of Sea Level Change Based on Improved Particle Swarm Optimization Neural Network Algorithm. Beijing Surveying and Mapping, 2023, 37(1): 131-136.

Wang Rugang, Liu Xuan, Zhou Feng, et al. Bearing Fault Diagnosis System and Method Based on Particle Swarm Optimization Integrated Neural Network. CN202211081326.2 [2023-09-02].

Guo Fuyang, Dong Wenfang, Zhang Yanwei. Research on Threat Assessment Method Based on PSO Improved RBF Neural Network. Journal of Computer Science and Applications, 2023, 13(6): 7. DOI: 10.12677/CSA.2023.136127.

Liu Chenwei, Sun Jian, Lei Bingbing, et al. Task Scheduling Strategy for Energy Optimization of Cloud Data Centers Based on Improved Particle Swarm Algorithm. Journal of Computer Science, 2023, 50(7): 246-253. DOI: 10.11896/jsjkx.220900176.

Shi Ruibo, Fu Zihao, Zhu Bo, et al. Ray Tracing Optimization Method for Outdoor Electrical Field Based on Particle Swarm Algorithm. Journal of Electromagnetic Wave Science, 2023, 38(1): 8.

Wang Xu, Zhang Wen, Chai Hongzhou. BDS-3 Satellite Clock Bias Prediction Based on Particle Swarm Optimization Neural Network Model. Journal of Chinese Inertial Technology, 2023, 31(1): 33-39.

Guo Yangheng, Zhang Yongfu. Research on Fault Diagnosis of Bearings Based on Particle Swarm Optimization RBF Neural Network. Information and Computer, 2023, 35(3): 89-92.

Zhang Jing. Optimization Model of Financial Management Early Warning for Neural Network Based on Chaotic Particle Swarm Algorithm. Microcomputer Applications, 2023, 39(2): 20-23.

Hu Wentao, Li Hua, Zheng Dong, et al. Optimization of Operation and Vibration Performance of Permanent Magnet Synchronous Motor Based on Neural Network and Particle Swarm Algorithm. Micro Special Electric Machines, 2023, 51(2): 26-30.

Yang Yang, Li Fengyong. Short-Term Load Forecasting Based on Gaussian Mutation Particle Swarm Optimization. Computer Simulation, 2023, 40(1): 125-130.

Wu Jigang, Wen Gang. Rolling Bearing Fault Diagnosis Method Based on Optimized Multiscale Permutation Entropy and Convolutional Neural Network. Spacecraft Environment Engineering, 2023, 40(1): 99-106.